High-growth firms and technological knowledge: do gazelles follow exploration or exploitation strategies?

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ABSTRACT.

This paper analyses the contribution of high-growth firms to the process of knowledge creation. We articulate a demand-pull innovation framework in which knowledge creation is driven by sales growth, and knowledge stems from creative recombination. Building on the literature on high growth firms and economic growth, we investigate whether 'gazelles' follow patterns of knowledge creation dominated by exploration or exploitation strategies. We construct indicators for the structure of knowledge and identify firms' innovation strategies. The empirical results show that increasing growth rates are associated with exploration, supporting the idea that high growth firms are key actors in the creation of new technological knowledge, and showing also that firms that achieve higher than average growth focus on exploration based on familiar technology. This suggests that exploration is less random than has been suggested. Our main result is that high growth firms, especially gazelles, predominantly adopt exploration strategies that have the characteristics of organized search more often observed among firms following an exploitation strategy.

Keywords: Gazelles; Recombinant Knowledge, Schumpeterian innovation patterns

JEL Classification Codes: L20, L10, 032

1 Introduction

The process of firm growth has long fascinated economists. Most empirical work draws on the seminal paper by Gibrat (1931), who proposed that firm growth is predominantly a random process (see Lotti, Santarelli and Vivarelli, 2003, 2009).

In recent years, analysis of firm growth has gained momentum, with particular attention on the distributional properties of firm growth rates, their persistence over time, and their determinants (Bottazzi and Secchi, 2006; Coad, 2007; Coad and Hölzl, 2011, Parker et al., 2010; Acs and Mueller, 2008; Lee, 2010).

Much of the focus of empirical work on the determinants of firm growth has shifted to analysis of firms showing growth rates that are much higher than the average. Henrekson and Johansson (2010) point out that this strand in the literature derives from Birch's (1979, 1981) contributions, which describe high growth firms as 'gazelles'. Birch maintains that these gazelles are the main source of job creation in the economic system. Understanding the conditions that make firms gazelles and the channels through which they contribute to the dynamics of aggregate economic growth could help policymakers to devise targeted supporting policy measures (Nightingale and Coad, 2014).

The analysis of the relationship between innovation and faster rates of growth is a more recent exercise, conducted mostly within empirical settings and based on quantile regressions (Coad and Rao, 2008 and 2010; Hoelzl, 2009).

This literature uses firm growth as a dependent variable, and attempts to understand what are the main factors affecting the outperforming behaviour of gazelles. When other dependent variables (such as R&D, see Coad and Rao, 2010) are taken into account, estimation of quantile regressions assigns firms to different classes according to rate of growth of R&D expenditure rather than firm growth. Therefore, the contribution of gazelles to innovation dynamics is still unclear.

In this paper we try to fill this gap by investigating the differential contribution of high-growth firms to the creation of technological knowledge. The literature on gazelles indeed emphasizes that their economic contribution is due mostly to the process of creative destruction that they engender, so that the net job creation ascribed to high growth firms stems from an ongoing dynamic process in which new opportunities emerge and likely replace obsolete activities (Hölzl, 2009, 2010; Henrekson and Johansson, 2010; Daunfeldt and Elert, 2013).

We are especially interested in the extent to which gazelles can be thought as featuring the population of firms in sectors dominated by Schumpeterian Mark I or Mark II patterns of innovation (Malerba and Orsenigo, 1995, 1997). Whether gazelles can be considered hybrids in relation to their innovation patterns is one of the main research questions investigated here. We combine a demand-pull innovation background with an approach to technological knowledge that emphasizes its collective and recombinant nature, and allows the identification of properties that characterize innovation strategies as random screening or organized search (Krafft, Quatraro and Saviotti, 2009). While a similar approach has been used to analyse productivity performance at various levels (Nesta, 2008; Quatraro, 2010; Antonelli, Krafft and Quatraro, 2010, Colombelli, Krafft and Quatraro, 2013), there are no studies to date that use it to investigate high-growth firms.

Our results show that gazelles cannot be strictly categorized as belonging to one mode or the other, but would appear to represent a mix, adopting a combination of exploration and organized search strategies.

The rest of the paper is organized as follows. Section 2 presents the theoretical underpinnings of the analysis, and outlines the working hypotheses. Section 3 describes the data and the methodology, with particular emphasis on the implementation of knowledge related indicators. Section 4 presents and discusses the empirical results and Section 5 concludes.

2 High-growth firms and technological knowledge: a Schumpeterian story?

There is a large literature on innovation. It consists of two main strands, one emphasizing the importance of the accumulation of skills and scientific knowledge as the drivers of innovation, the other emphasizing the role of economic mechanisms on the demand side. The first strand is usually described as technology-push and the second as demand-pull.

The pioneer of the demand-pull approach in its modern form was Jacob Schmookler.[2] He observed how time series on technology creation, proxied by patent applications, tended to follow time series on output (Schmookler, 1954, 1962). He interpreted this as that "more money will be available for invention when the industry's sales are high than when they are low. Increased sales imply that both the producing firms and their employees will be in a better position than before to bear the expenses of invention" (Schmookler, 1962: p.17). In this framework, the ability to finance knowledge creation activities plays a central role (Schmookler, 1966). Empirical analyses of the effects of firm performance on knowledge creation have been confined to the level of innovation, without any attempt to qualify the patterns of innovation (Griliches and Schmookler, 1963; Scherer, 1982; Crespi and Pianta, 2007 and 2008).

In this context, the identification of two distinct Schumpeterian patterns of innovation by Malerba and Orsenigo (1995, 1997) is useful. They describe Schumpeter Mark I as characterized by 'creative destruction', ease of entry and the emergence of new firms based on business opportunities, which challenge incumbents and continuously disrupt current modes of production, organization and distribution. Schumpeter Mark II is characterized by 'creative accumulation', the relevance of industrial R&D laboratories and the key role of large firms. The authors also apply the labels of 'widening' and 'deepening' to these patterns. The former description applies to an innovative base

[2] Of course, the seeds of the argument go back to Adam Smith (1776), who emphasized the indirect effects of increasing demand on technological change through the positive effects of the division of labour. This argument was developed and integrated by Marshall (1890) and Young (1928).

that is continuously growing, the latter describes accumulation strategies based on existing technological premises. In this direction, the positive relationship between firms' growth and innovation may either be channeled by Schumpeter Mark I or Schumpeter Mark II dynamics.

The grafting of the recombinant knowledge approach onto the investigation of the relationship between high-growth firms and patterns of innovation may be far reaching. While traditional approaches to technological knowledge tend to represent it as a homogeneous stock (Griliches, 1979; Mansfield, 1980), according to recombinant knowledge approach, the creation of new knowledge can be represented as a search process across a set of alternative components that can be combined with one another. Here the cognitive mechanisms underlying the search process are important for exploring the knowledge space to identify which pieces of knowledge might be combined (Weitzmann, 1998; Kauffman, 1993). The set of potentially combinable pieces is a subset of the whole knowledge space. Search is supposed to be local rather than global; influenced by cognitive, social and technological factors. The ability to engage in a search process in more distant spaces is likely to generate breakthroughs based on combinations of new components (Nightingale, 1998; Fleming, 2001).

If knowledge stems from the combination of different technologies, a firm's knowledge base can be represented as a web of connected elements. The nodes of this network represent the elements of the knowledge space that could be combined, while the links represent their actual combination. The frequency with which two technologies are combined provides useful information for how we characterize the internal structure of the knowledge base. Such characterization takes account of the average degree of complementarity of the technologies comprising the knowledge bases, and also the variety of the observed pairs of technologies, which allows us to define three properties of knowledge structure:

- **Knowledge Variety** is related to technological differentiation within the knowledge base, in particular with respect to the possible different combinations of pieces of knowledge in the sector, from the creation of radically new types of knowledge to more incremental recombinations of already existing types of knowledge.

- **Knowledge Coherence** can be defined as the extent to which the pieces of knowledge that agents within the sector combine to create new knowledge are complementary.
- **Knowledge Similarity** refers to the extent to which the pieces of knowledge used in the sector are close in the technology space.

The dynamics of technological knowledge, therefore, can be understood as the patterns of change to its internal structure, that is, the patterns of recombination across the elements in the knowledge space. This captures the cumulative character of knowledge creation and the key role played by the properties describing knowledge structure, and also the possible link to the relative stage of development in the technological trajectory (Dosi, 1982; Saviotti, 2004, 2007; Krafft, Quatraro and Saviotti, 2009).

This approach allows a better distinction between innovation strategies, that is, between exploration and exploitation (March, 1991). The view of knowledge as an outcome of a recombination activity allows the idea of two nested dimensions, defined according to the degree to which agents decide to rely on exploration or exploitation, or a combination of the two, which has suggested concepts such as 'search depth' and 'search scope' (Katila and Ahuja, 2002). Search depth refers to degree to which agents draw upon prior knowledge, search scope refers to the degree to which agents rely on the exploration of new areas in the knowledge space.

Combining the demand-pull framework with the recombinant knowledge approach and analysis of Schumpeterian patterns of gazelles' innovation activities, allow us to refine our main working hypotheses as follows.

Sales growth is a key factor in high levels of innovations. For this reason, gazelles are expected to be characterized by demand-driven dynamics of knowledge creation based on search behaviours aimed at widening or deepening the firm's technological competences. Our main research question is whether the important contribution of gazelles to economic growth can be ascribed to search behaviours typical of a Schumpeter Mark I pattern of innovation activities or a Schumpeter Mark II pattern. In the first pattern, the positive impact of high-growth firms is based on their capacity to undertake search behaviours directed towards the exploration of untried technological fields, which broadens the existing knowledge base initially in a rather random way. Extending the knowledge base means extending beyond the boundaries of what the firm already knows. Exploration tends to be a key part of the destructive creativity of gazelles that follow a widening pattern. The search behaviour of high-growth firms can be expected to depart to some extent from established trajectories to discover new fields in the technology landscape in order to increase search scope. According to this pattern, search behaviours will be more focused on a range of 'successful' technological fields, leading to a deepening of the existing knowledge base. Exploitation is intended to combine knowledge in a more organized way, and is likely to apply to high growth firms.

Figure 1 maps the paths followed by gazelles, distinguishing between: i) strategies (exploration versus exploitation); and ii) the way they implement these strategies (random search versus organized search). The result is a two-by-two conceptual matrix, with a horizontal axis (strategies) and a vertical axis (type of search).

Figure 1 allows us to visualize the typical Schumpeterian Mark 1 and Mark 2 patterns of innovation (1^{st} and 3^{rd} quarter). In Mark 1, firms are depicted as developing different characteristics of product innovation, in a situation of high uncertainty, which implies a predominance of trial and error system of development; in Mark 2, firms draw on their experience, which reduces uncertainty, in selecting the ways to innovate successfully. After a period of exploration where firms try several possible combinations to produce innovation, there is a period of more stabilized choice around a smaller set of possibilities.

>>> INSERT FIGURE 1 ABOUT HERE <<<

Gazelles do not necessarily follow pure models of innovation patterns. Due to their multifaceted characteristics in terms of size, innovation behaviour, etc., it is necessary to consider them in a dynamic framework where they may evolve from one model to another (e.g. from Mark 1 to Mark 2), or extend the characteristics of one model to overlap with characteristics assumed to belong to the other model. For instance, gazelles may be small firms, highly oriented towards a model of innovation by exploration, but they may pursue this strategy in a more organized way than predicted by Mark 1. Alternatively, large gazelle firms, which engage in an exploitation strategy (i.e. Mark 2 characteristics), may adopt some random screening activities that combine pieces of knowledge that are usually exclusively attributed to Mark 1.

There is a growing literature on the relation between diversity in the knowledge base and the performance of firms (see also Ostergaard et al., 2011, for an investigation of the relationship between diversity in intangible assets and innovation), but the present paper is the first attempt to study the link between high growth firms and knowledge base heterogeneity, based on the properties of variety, coherence and similarity of the knowledge base.

In the next section we describe the data and the methodology used to provide an operational definition of the concept of recombinant knowledge and the properties of knowledge structure, and to characterize the search behaviour of high-growth firms.

3 Data, Variables and Methodology

3.1 Dataset

The dataset is an unbalanced panel of publicly traded firms in UK, Germany, France, Sweden, Italy and the Netherlands. Our main source of market and accounting data is Thomson Datastream. To obtain additional relevant variables, we include in the dataset information collected from AMADEUS by Bureau Van Dijk. The period of observation for all the countries examined is 1988 to 2005. We also use data from the OECD REGPAT database, which provides regional information on the addresses of patent applicants and inventors as well as on technological classes cited in patents granted by the European Patent Office (EPO) and the World Intellectual Property Organization (WIPO), under the Patent Co-operation Treaty (PCT), from 1978 to 2006.

In order to match the firm level data with data on patents, we draw on the work of Thoma et al. (2010), which develops a method for harmonization and combination of large-scale patent and trademark datasets with other sources of data, through standardization of applicant and inventor names.

We pooled the dataset by adding industry level information from the OECD STAN database. STAN is based on ISIC revision 3 sectoral classifications; Thomson Datastream uses the four digit level ICB industry classification (Appendix B provides the sectoral concordance table used to link the two classifications).

Our final dataset is an unbalanced panel of 335 active companies listed on the main European financial market that submitted at least one patent application to the EPO in the period analysed.[3] Table 1 reports the sample distribution by macro-sector, country and size classes. High and medium-high technology firms account for around 30% and 37% of observations, respectively. Medium low and low technology firms account for 3% and 10% respective, and knowledge intensive firms represent some 7% of observations. The other economic groups each account for less than 10% of the observations.

>>>INSERT TABLE 1 ABOUT HERE<<<

As expected, most of the sampled firms (80.9%) are large firms, that is, firms with more than 250 employees; 13.43% of the sample is medium sized firms. The country distribution is more diverse,

[3] This relatively small number of firms is the outcome of merging the dataset with company-level information and patent applications. They are firms that are listed on the relevant markets and which submitted more than 1 patent application during the observed period. The firms in the sample are observed for at least 6 years for the sales variable. Average observation time is 9.4 years.

although 34% of the sampled firms are German and 25% are French. Sweden and the UK follow with 13% and 14% of sampled firms respectively.

3.2 The Variables

Since we are interested in the dynamic aspects of the relationship between sales and knowledge creation, we use the growth rates of the relevant variables. At the general level, growth rates can be defined as follows:

$$Growth_{i,t} = \ln(X_{i,t}) - \ln(X_{i,t-1}) \qquad (1)$$

where *X* is measured as sales, knowledge capital stock, knowledge coherence, cognitive distance, knowledge variety, related knowledge variety and unrelated knowledge variety. All these variables are explained below and in Appendix A, and are calculated for firm *i* at time *t*. In line with previous empirical work (Bottazzi et al., 2010; Coad, 2011), the growth rate distributions are normalized around zero in each year by removing the means as follows:

$$s_{i,t} = Growth_{i,t} - \frac{1}{N}\sum_{i=1}^{N} Growth_{i,t} \qquad (2)$$

where *N* is the total number of firms in the sample. This procedure effectively removes average time trends common to all the firms caused by factors such as inflation and business cycles.

3.2.1 Knowledge Indicators

To define our knowledge related variables, we start with the firm's knowledge stock. This is computed by applying the permanent inventory method to patent applications. We calculate it as the cumulated stock of patent applications using a rate of obsolescence of 15% per annum: $E_{i,t} = \dot{h}_{i,t} + (1-\delta)E_{i,t-1}$, where $\dot{h}_{i,t}$ is the flow of patent applications and δ is the rate of obsolescence.

Implementation of knowledge characteristics proxying for variety, coherence and similarity, rests on the recombinant knowledge approach. In order to provide an operational translation of these variables we need to identify a proxy for the bits of knowledge, and a proxy for their structural elements. We could use scientific publications as a proxy for knowledge, and use keywords or scientific classification (e.g. the JEL code for economists) to proxy for knowledge structure. However, we chose to use patents as a proxy for knowledge, and use the technological classes to which the patents are assigned as structural elements, that is, the nodes in the network representation of recombinant knowledge.[4] Each technological class *j* is linked to another class *m* if the same patent is assigned to both classes. The higher the number of patents assigned to both classes *j* and *m*, the stronger is the link. Since the technological classes attributed to patents are reported in the patent documents, we refer to the link between *j* and *m* as their co-occurrence within the same patent document.[5] This allows us to calculate the following three characteristics of the firm's knowledge bases (see appendix A for methodological details):

a) Knowledge variety (KV) measures the degree of technological diversification of the knowledge base. It is derived from the information entropy index and can be decomposed into related knowledge variety (RKV) and unrelated knowledge variety (UKV).
b) Knowledge coherence (COH) measures the degree of complementarity among technologies.
c) Cognitive distance (CD) expresses knowledge dissimilarities amongst different types of knowledge.

[4] The limitations of patent statistics as indicators of technological activities are well known. They include sector-specificity, existence of non-patentable innovations and the fact that they are not the only means of protection. Also, the propensity to patent tends to vary over time as a function of the cost of patenting, and is more frequent in large firms (Pavitt, 1985; Griliches, 1990). However, previous studies highlight the utility of patents as a measure of the production of new knowledge. Studies show that patents are very reliable proxies for knowledge and innovation compared to analyses that use data from surveys on the dynamics of process and product innovation (Acs et al., 2002). Alongside the debate on patents as outputs rather than inputs of innovation activity, empirical analyses show that patents and R&D are dominated by a contemporaneous relationship, providing further support for patents to proxy for technological activities (Hall et al., 1986).

[5] Note that to compensate for intrinsic volatility in patenting behaviour, patent applications refer to the last five years.

Use of these variables represents progress in the operational translation of knowledge creation processes. They deal explicitly with the heterogeneity of knowledge and allow a better appreciation of the collective dimension of knowledge dynamics. Knowledge is viewed as the outcome of combinatorial activity in which intentional and unintentional exchange among innovating agents provides access to external knowledge inputs (Fleming et al., 2007). The network dynamics of innovating agents constitute a foundation for the emergence of new technological knowledge, which in turn is represented as organic in structure, characterized by elementary units and the connections amongst them. The use of these variables implies a mapping between technology as an activity and technology as an artefact (Arthur, 2009; Lane et al., 2009; Krafft and Quatraro, 2011). Co-occurrence matrices are similar to design structure matrices (DSM) (Baldwin and Clark, 2000; Murmann and Frenken, 2006; Baldwin, 2007), in that they can be considered adjacency matrices in which our interest is in both the link between the elements and the frequency of these links.

In other words, these measures capture the design complexity of the knowledge structure, and allow observation of firm behaviour in relation to innovation, and its evolution with the changing architecture of the knowledge structure (Henderson and Clark, 1990; Murmann and Frenken, 2006). In this perspective, knowledge variety is likely to increase when new combinations of knowledge are introduced into the system. However, the balance between related and unrelated variety should be such that related variety dominates during the exploitation phase and unrelated variety dominates in exploration phases (Krafft, Quatraro, Saviotti, 2009). An increase in knowledge coherence is likely to signal the change to an exploitation strategy, while a decrease is likely to be linked to an exploration strategy. Increasing values for cognitive distance are likely to be related to random screening of the technology landscape, while decreasing cognitive distance is likely to be linked to organized search behaviour. Looking again at Figure 1, and bearing in mind the above trends, we can interpret the innovation behaviour of high growth firms. The inner boxes provide some clues about the expected signs of the knowledge variables for different innovation patterns.

The next section discusses the results of the empirical analysis.

3.2.2 Descriptive statistics

Figure 2 shows the distribution of firms' growth rates, for all the relevant variables. The empirical distribution of growth rates seems closer to a Laplacian than to a Gaussian distribution. This is in line with studies analysing the distribution of firm growth rates (Bottazzi et al., 2010; Bottazzi and Secchi, 2003; Castaldi and Dosi, 2009). Table 2 reports the descriptive statistics for knowledge indicators and the other variables in our model, expressed as growth rates normalized according to Equation 2. The values on kurtosis and on the percentiles confirm that growth rates are characterized by fat tailed (although highly skewed) distributions.

>>>INSERT FIGURE 2 AND TABLE 2 ABOUT HERE<<<

This suggests that standard regression estimators, such as ordinary least squares (OLS), and assuming Gaussian residuals, may perform poorly if applied to these data. To cope with this, a viable and increasingly popular alternative is to implement least absolute deviation (LAD) techniques, which are based on minimizing the absolute deviation from the median, rather than the squares of the deviation from the mean.

Figure 3 depicts the distribution of firm sales growth by macro-sector (see Appendix B for the definitions of macro-sectors). It shows that firm growth rates are highly dispersed in high-tech sectors and that the dispersion decreases from high-tech to low-tech sectors. Knowledge intensive sectors (denoted KIS) show highly dispersed growth rates.

>>>INSERT FIGURE 3 ABOUT HERE<<<

Table 3 presents the matrix of correlations among the variables used for the empirical exercise, at a significance level of 1%. Although some significant patterns of correlation can be identified, these involve mostly the variety-related variables, and (except for the three variety measures, which, as expected, are characterized by non-negligible correlations) the coefficients are not high enough to generate huge concern.

>>>INSERT TABLE 3 ABOUT HERE<<<

3.3 Methodology

Many of the empirical works analysing the determinants of firm growth are based on Gibrat's Law, which holds that firm growth is independent of firm size. However, some scholars claim that Gibrat's Law cannot be assumed to be a general law and its validity cannot be taken for granted *ex ante* (see Lotti, Santarelli and Vivarelli, 2003 and 2009). Some studies find that growth rates are autocorrelated.

The original contribution of the present paper is that we reverse the traditional line of reasoning by adopting a demand-pull approach in which sales growth provides the incentive to commit resources to knowledge creation activities. Thus, our empirical strategy differs from other empirical work in the field based on the seminal contributions of Griliches and Schmookler (1963) and Scherer (1982). We directly test the effect of sales growth rates on knowledge creation, emphasizing the demand pull side of innovation. Another novelty of our approach is that we are not interested so much in understanding whether increasing sales affect the level of knowledge creation. Rather we investigate the qualitative aspects of the knowledge creation process by examining the properties of knowledge structure (i.e. variety, coherence and similarity). Our empirical implementation is described in the next section. It distinguishes the present analysis from contributions in the Schmooklerian tradition, and work that emphasizes the relative weak effect of firm sales on R&D intensity (see e.g. Pakes and Schankerman, 1977, 1984).

We are interested in the extent to which knowledge is (or is not) a determinant of firm growth, and whether the properties of the knowledge structure are related to one another and to the level of knowledge creation. An empirical strategy that investigates coevolution of the series is useful in not imposing any a priori relationship amongst the variables at stake. In order to identify the potential co-evolutionary patterns of the interdependent variables we implement the analysis in a (reduced form) vector autoregression (VAR) model (Coad, 2010). First, recall the generic operational definition of the variables we use in the analysis s_{it}, that is, growth rate detrended through normalization. The baseline VAR model can then be written as:

$$s_{i,t} = a + \beta s_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where s_{it} is an m×1 vector of the random variables for firm *i* at time *t*, β is an m×m matrix of the slope coefficients to be estimated. In our case m=7 and corresponds to the vector [sales growth (i,t), knowledge capital growth (i,t), coherence growth (i,t), increase in cognitive distance (i,t), increase in variety (i,t), growth of related variety (i,t), growth of unrelated variety (i,t)]. ε is an m×1 vector of disturbances. The 7 structural equations are therefore the following (the variables has to be understood as normalized growth rates according to equation (2)):

$$Sales_{i,t} = a_1 + \beta_{1,1}Sales_{i,t-1} + \beta_{1,2}E_{i,t-1} + \beta_{1,3}COH_{i,t-1} + \beta_{1,4}CD_{i,t-1} + \beta_{1,5}TV_{i,t-1} + \beta_{1,6}RTV_{i,t-1} + \beta_{1,7}UTV_{i,t-1} + \varepsilon_{1,i,t} \quad (3a)$$
$$E_{i,t} = a_2 + \beta_{2,1}Sales_{i,t-1} + \beta_{2,2}E_{i,t-1} + \beta_{2,3}COH_{i,t-1} + \beta_{2,4}CD_{i,t-1} + \beta_{2,5}TV_{i,t-1} + \beta_{2,6}RTV_{i,t-1} + \beta_{2,7}UTV_{i,t-1} + \varepsilon_{2,i,t} \quad (3b)$$
$$COH_{i,t} = a_3 + \beta_{3,1}Sales_{i,t-1} + \beta_{3,2}E_{i,t-1} + \beta_{3,3}COH_{i,t-1} + \beta_{3,4}CD_{i,t-1} + \beta_{3,5}TV_{i,t-1} + \beta_{3,6}RTV_{i,t-1} + \beta_{3,7}UTV_{i,t-1} + \varepsilon_{3,i,t} \quad (3c)$$
$$CD_{i,t} = a_4 + \beta_{4,1}Sales_{i,t-1} + \beta_{4,2}E_{i,t-1} + \beta_{4,3}COH_{i,t-1} + \beta_{4,4}CD_{i,t-1} + \beta_{4,5}TV_{i,t-1} + \beta_{4,6}RTV_{i,t-1} + \beta_{4,7}UTV_{i,t-1} + \varepsilon_{4,i,t} \quad (3d)$$
$$TV_{i,t} = a_5 + \beta_{5,1}Sales_{i,t-1} + \beta_{5,2}E_{i,t-1} + \beta_{5,3}COH_{i,t-1} + \beta_{5,4}CD_{i,t-1} + \beta_{5,5}TV_{i,t-1} + \beta_{5,6}RTV_{i,t-1} + \beta_{5,7}UTV_{i,t-1} + \varepsilon_{5,i,t} \quad (3e)$$
$$RTV_{i,t} = a_6 + \beta_{6,1}Sales_{i,t-1} + \beta_{6,2}E_{i,t-1} + \beta_{6,3}COH_{i,t-1} + \beta_{6,4}CD_{i,t-1} + \beta_{6,5}TV_{i,t-1} + \beta_{6,6}RTV_{i,t-1} + \beta_{6,7}UTV_{i,t-1} + \varepsilon_{6,i,t} \quad (3f)$$
$$UTV_{i,t} = a_7 + \beta_{7,1}Sales_{i,t-1} + \beta_{7,2}E_{i,t-1} + \beta_{7,3}COH_{i,t-1} + \beta_{7,4}CD_{i,t-1} + \beta_{7,5}TV_{i,t-1} + \beta_{7,6}RTV_{i,t-1} + \beta_{7,7}UTV_{i,t-1} + \varepsilon_{7,i,t} \quad (3g)$$

Since we are interested in the differential impact of high growth firms, we use indicator variables. First, we build a simple dummy variable, which we call HGF, which identifies gazelles as firms whose average growth rate is at least 20% over the whole period.[6] This identifies 116 out of 335 firms as

[6] Our data do not contain information on firm age; so we cannot use this in defining high growth firms. We acknowledge that high growth firms may be the result of rather heterogenous growth patterns. For example, merger and acquisition may introduce some noise in their identification (Delmar et al., 2003). Unfortunately, our dataset did not allow us to check for the influence of these issues.

high growth and allows us to investigate shifts in the intercept in the estimated equations for gazelles. We calculate the interaction variable [HGF×sales growth(t-1)], which allows us to detect any modification in the slope coefficient of sales growth of gazelles.

Following Coad (2010), we do not include individual dummies in the analysis. Although unobserved heterogeneity, due, for example, to sector of activity, location, etc., can have important effects on the estimation results, the inclusion of firm-specific dummies along with lagged variables could produce biases in the fixed-effects estimation of the dynamic panel-data models, a problem known as Nickell-bias. An alternative approach would be to use instrumental variables (IV) or GMM estimators (Blundell and Bond, 1998). However, it is difficult to find good instruments, particularly when dealing with growth rates. If the instruments are weak, IV estimation of panel VAR could lead to imprecise estimates. Binder et al. (2005) propose a panel VAR model including firm-specific effects, which is based on the assumption of normally distributed errors, but this assumption does not apply to the growth rates of the variables in our regressions.

Since we are dealing with rates rather than levels of growth, in our view any firm-specific components have been mostly removed. We follow the large literature on analysis of firm growth rates which states that the non-Gaussian nature of growth rate residuals is a more important econometric problem and deserving of careful attention.

In view of this, equation (3) is estimated via reduced form VARs, to avoid any ex ante definition of the causal structure on the relationships between variables. Reduced form VARs correspond to a series of *m* individual regressions. Given the distributional properties of the variables, we prefer to implement LAD estimators.

4 Discussion of Empirical Results

Table 4 reports the results of the VAR estimation for the baseline model[7]. The rows correspond to the regressions in the vector autoregression model. The columns present the differential effect of each (lagged) explanatory variable on each dependent variable. For the purposes of the present paper the first column contains the most important information because it shows the effect of lagged sales growth rates on the seven model variables. However, it should be noted that all the coefficients along the diagonal of the matrix are statistically significant, and with the exception of sales and knowledge capital, are negative. This suggests that while growth of knowledge properties shows little persistence, we observe some persistence in the case of sales and even more in the case of knowledge capital. This result contrasts with previous findings (Coad, 2007, 2011) showing that the lagged values of sales growth has a negative effect on present values. However, this difference may be due to a peculiarity of the sampled firms, which is that they are all publicly listed and, therefore, may be affected by positive performance in final markets.

>>> INSERT TABLE 4 ABOUT HERE <<<

In relation to the coefficients, in the first column we observe a positive relationship between lagged sales growth and knowledge capital. This provides further support for the demand pull hypothesis according to which increasing sales provide firms with the resources required for the production of technological knowledge. For the effects on the properties of knowledge structure, we find that sales growth is negatively related to knowledge coherence and cognitive distance, but positively related to total variety. This suggests that the more firms grow, the more likely that their technology portfolios will show more variety. Technological variety is characterized by low levels of complementarity (coherence) (which supports the idea of an exploration strategy) but also by low levels of dissimilarity. This would suggest that increasing sales growth is associated with exploration directed

[7] The models discussed in this section have also been estimated by using OLS. The results obtained are similar to those obtained with LAD estimations in terms of coefficients' signs and significance, especially for what concerns the HGF dummy.

towards the discovery of new, complementary fields that are not too distant from the firm's existing technological competences.

In order to understand whether high-growth firms show idiosyncratic patterns, Table 5 includes the dummy HGF as a regressor in all the VAR equations. If we look at the first two columns in Table 5, we can see that the results for patterns of persistence of the observed variables do not vary much. Note also that the effects of sales growth on these patterns are similar to the effects in Table 4. Increasing sales growth rates stimulates rates of growth of knowledge capital and knowledge variety, achieved by the adoption of search strategies directed to exploring new complementary fields that are still close to the firm's existing technological capabilities.

>>> INSERT TABLE 5 ABOUT HERE <<<

If we look at the HGF dummy, we see that, as expected, the coefficient of sales growth is positive and significant. It is also positive and significant for rate of growth of knowledge capital, suggesting that the economic influences on knowledge creation operating via the demand side are even stronger in the case of gazelles. If we look at the effects on the properties of knowledge structure, we find that the dummy is significant only in the case of cognitive distance, where the coefficient is negative. This suggests that, provided that increasing growth rates are associated with a reduction in cognitive distance, high growth firms tend to adopt search strategies characterized, on average, by lower levels of dissimilarity. The dummy does not show any other significant effects on the knowledge variables.

In Table 6, we include the interaction variable [sales growth(t-1)×HGF]. The pattern does not change much in relation to rates of growth rates of the variables under scrutiny; the coefficient relating the lagged to the present value of each of the properties of knowledge structure is negative and significant, but the sign on knowledge capital is positive and significant.

>>> INSERT TABLE 6 ABOUT HERE <<<

The effect of lagged sales growth on knowledge is in line with the previous estimates, suggesting that increasing growth rates are likely to provide economic incentives for the commitment of resources for knowledge creation activities. Even in this case, the patterns of effects on the properties of the knowledge base confirm that increasing growth rates lead to the introduction of knowledge variety through exploration strategies directed towards the widening of complementary technologies (coherence), which are similar to the existing technology portfolio. This interpretation is supported also by the positive and significant coefficient of related variety.

Columns 2 and 3 of Table 6 refer to the subgroup of high growth firms. The coefficients of the dummy variable suggest that it promotes higher rates of growth of knowledge capital. In addition, and importantly, gazelles are characterized on average by lower rates of growth of coherence, which is consistent with the tendency to adopt exploratory behaviours, although the negative coefficient of sales growth is mitigated by the coefficient of the interaction variables. That is, high growth firms on average tend to adopt exploration strategies, although in that subgroup increasing rates of growth do not lead to consistent variations in this behaviour. The value and the negative sign of the variety variables confirms that increasing growth rates in the group of gazelles are associated with fairly stable technological variety.

The analysis would seem to support the idea that gazelles cannot be unambiguously categorized as Schumpeter Mark I or Mark II innovating firms. They seem to follow a hybrid pattern of search behaviour, characterized both by exploration and implementation of organized search strategies. Thus, gazelles are associated more with an organized exploration pattern, and would fit in the bottom-left quadrant of Figure 1. On average, increasing sales growth rates stimulate the creation of new technological knowledge through the adoption of search behaviours directed more to screening new complementary fields, which are compatible with an exploration strategy. However, the screening activity is not random: it seems that fast growing firms prefer to remain reasonably close to their existing technological competences. In the group of gazelles this pattern of behaviour is especially marked since they appear to be characterized by lower rates of growth of coherence and cognitive distance, and related variety on average. We find therefore, that high growth firms, and especially gazelles, predominantly follow exploration strategies that have some of the characteristics of organized search more typical of an exploitation strategy.

5 Conclusions

The process of firm growth has attracted the attention of economists for many years. A relatively recent strand in the literature on high-growth firms refers to gazelles or fast growing firms, based on evidence of their exceptional contribution to aggregate economic growth. However, few studies look at the relationship between high-growth firms and innovation. The literature mostly analyses innovation as a determinant of high rates of growth. There are no studies of the contribution made by gazelles to the process of knowledge creation.

The main objective of this paper was to investigate the differential contribution of high growth firms to the process of knowledge creation drawing on the literature on Schumpeterian patterns of innovation to construct a demand-pull framework *à la* Schmookler in which sales growth is the motivation for the creation of new technological knowledge. We investigated whether gazelles are more likely to follow Mark I or Mark II patterns of knowledge creation.

The inclusion of recombinant knowledge theory in our framework allowed us to propose the concept of knowledge structure characterized by three properties - variety (related and unrelated), coherence, and similarity - which can be usefully employed to distinguish between ‘random screening’ and ‘organized search’ strategies.

The analysis was based on data on listed companies and patent applications. We implemented a series of VARs estimated by means of LAD estimators, including a dummy and interaction variable to detect differential performance by gazelles. The empirical results suggest that within the group of high growth firms, increasing sales growth rates stimulate the creation of new technological knowledge and also drive search behaviours characterized by the screening of complementary fields across the technology landscape that are not too far removed from the firm's existing technological competences. In this respect, the distinctive knowledge dynamics of gazelles are likely to shape their positive impacts on industry dynamics (Bos and Stam, 2014).

This paper is a first attempt to investigate the contribution of gazelles to the process of knowledge creation. Future work could analyse the relationship by splitting the sample according to different quantile definitions. Empirical implementations of knowledge coherence, such as in this paper, have been criticized by Bottazzi and Pirino (2010); it would be interesting to use the corrected index they propose, to check whether our results still hold. It would be interesting also to check the robustness of our results, by implementing different estimators to account for the distribution of explanatory variables and the impact of outliers.

Moreover, the evidence provided by this paper constitutes a basis for further interesting investigations, and especially in the domain of innovation and technology policies. Because high-growth firms are important knowledge producers, the dynamics leading them to be innovative and to take stock of their ability to broaden their knowledge bases, should be taken into account by policy makers. Moreover, they require special consideration as they are spread across all industries in the economy. Innovation policies should in this respect be careful and valorise the contribution made by gazelles through the processes of creative destruction.

6 References

Acs, Z., Anselin, L. and Varga, A. (2002), 'Patents and Innovation Counts as Measures of Regional Production of New Knowledge,' *Research Policy*, 2002, **31**(7), 1069-1085.

Acs, Z. and Mueller, P. (2008), 'Employment effect of business dynamics: mice, gazelles and elephants,' *Small Business Economics*, **30**, 85-100.

Antonelli, C., Krafft, J. and Quatraro, F. (2010), 'Recombinant Knowledge and Growth: The Case of ICTs,' *Structural Change and Economic Dynamics*, **21**(1), 50-69.

Arthur, W.B. (2009), *The Nature of Technology. What It Is and How It Evolves*. The Free Press: New York.

Attaran, M. (1985), 'Industrial diversity and economic performance in U.S. areas', *The Annals of Regional Science*, **20**, 44-54.

Baldwin, C. Y. (2007), 'Where do transactions come from? Modularity, transactions, and the boundaries of firms,' *Industrial and Corporate Change*, **17**, 155-195.

Baldwin, C. Y. and Clark, K.B. (2000), *Design Rules, Volume I, The power of Modularity*. The MIT Press: Cambridge MA.

Binder, M., C. Hsiao and C. H. Pesaran (2005), 'Estimation and inference in short panel vector autoregressions with unit roots and cointegration,' *Econometric Theory*, **21**, 795–837.

Birch, D. (1979), *The job generation process*. The MIT Press: Cambridge MA.

Birch, D. (1981), 'Who creates jobs?,' *The Public interest*, **65**(fall), 3-14.

Blundell R.W and Bond S.R. (1998), 'Initial conditions and moment restrictions in dynamic panel data models,' *Journal of Econometrics*, **87**, 115-143.

Bos, J. and Stam, E. (2014), ‘Gazelles and industry growth,’ *Industrial and Corporate Change*, this issue.

Boschma R. and Iammarino, S. (2009), ‘Related variety, trade linkages, and regional growth in Italy,’ *Economic Geography*, **85**, 289-311.

Bottazzi, G., Coad, A., Jacoby, N. and Secchi, A. (2011), ‘Corporate growth and industrial dynamics: evidence from French manufacturing,’ *Applied Economics*, **43**, 103-116.

Bottazzi, G. And Pirino, D. (2010), ‘Measuring Industry Relatedness and Corporate Coherence,’ LEM Working Paper 10/2010, Sant’Anna School of Advanced Studies, Pisa.

Bottazzi, G. and Secchi, A. (2006), ‘Explaining the Distribution of Firms Growth Rates,’ *Rand Journal of Economics*, **37**, 234–263.

Bottazzi, G., Secchi, A. (2003), ‘Common properties and sectoral specificities in the dynamics of U.S. manufacturing companies,’ *Review of Industrial Organization*, **23**, 217–232.

Breschi S., Lissoni, F. and Malerba, F. (2003), ‘Knowledge relatedness in firm technological diversification,’ *Research Policy*, **32**, 69-97.

Castaldi, C. and Dosi, G. (2009), ‘The patterns of output growth of firms and countries: Scale invariances and scale specificities,’ *Empirical Economics*, **37**, 475-495.

Coad, A. and Hölzl, W. (2011), ‘Firms growth: empirical analysis,’ in M. Dietrich and J. Krafft (eds), *Handbook on the economics and theory of the firm*. Edward Elgar: Cheltenham.

Coad, A. and Rao, R. (2008), ‘Innovation and firm growth in high tech sectors: a quantile regression approach,’ *Research Policy*, **37**(4), 633-648.

Coad, A. and Rao, R. (2010), ‘Firm growth and R&D expenditure,’ *Economics of Innovation and New Technology*, **19**(2), 127–145.

Coad, A. (2011), ‘Appropriate business strategy for leaders and laggards,’ *Industrial and Corporate Change*, **20**, 1049-1079.

Coad, A. (2010), 'Exploring the processes of firm growth: evidence from a vector auto-regression,' *Industrial and Corporate Change,* **19**, 1677-1703.

Coad, A. (2007), 'A Closer Look at Serial Growth Rate Correlation,' *Review of Industrial Organization*, **31**(1), 69–82.

Colombelli, A., Krafft, J. And Quatraro, F. (2013), 'Properties of knowledge base and firm survival: Evidence from a sample of French manufacturing firms,' *Technological Forecasting and Social Change*, **80**, 1469-1483.

Crespi, F. and Pianta, M. (2008), 'Demand and innovation in productivity growth,' *International Review of Applied Economics*, **22**, 655-672.

Crespi, F. and Pianta, M. (2007), 'Demand and Innovation in European Industries,' *Economia Politica*, 1/2007, 79-111.

Daunfeldt, S.O. and Elert, N. (2013), 'When is Gibrats law a law?,' *Small Business Economics*, **41**, 133-147.

Dosi, G. (1982), 'Technological paradigms and technological trajectories,' *Research Policy*, **11**, 147–162.

Fleming, L. (2001), 'Recombinant Uncertainty in Technological Search,' *Management Science* **47**(1), 117-132.

Fleming, L., Mingo, S. and Chen, D. (2007), 'Collaborative brokerage, generative creativity and creative success,' *Administrative Science Quarterly*, **52**, 443-475.

Frenken K., van Oort, F. and Verbug, T. (2007), 'Related Variety, Unrelated Variety and Regional Economic Growth,' *Regional Studies*, **41**(5), 685-97.

Frenken, K. and Nuvolari, A. (2004), 'Entropy Statistics as a Framework to Analyse Technological Evolution,' in J. Foster and W. Hölzl (eds), *Applied Evolutionary Economics and Complex Systems*. Edward Elgar: Cheltenham, U.K. and Northampton, Mass.

Gibrat, R. (1931), *Les inégalités économiques*. Recueil Sirey, Paris.

Griliches, Z. (1979), 'Issues in assessing the contribution of research and development to productivity growth,' *The Bell Journal of Economics*, **10**, 92-116.

Griliches, Z. (1990), 'Patent statistics as economic indicators: a survey,' *Journal of Economic Literature*, **28**, 1661-1707.

Griliches, Z. and Schmookler, J. (1963), 'Inventing and maximizing,' *American Economic Review*, **53**, 725-29.

Hall, B.H., Griliches Z. and Hausman J.A. (1986), 'Patents and R and D: Is there a lag?,' *International Economic Review*, **27**, 265-283.

Henderson, R.M and Clark, K.B. (1990), 'Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms,' *Administrative Science Quarterly*, **35**, 9-30.

Henrekson, M. and Johansson, D. (2010), 'Gazelles as Job Creators - A Survey and Interpretation of the Evidence,' *Small Business Economics*, **35**(2), 227-244.

Hölzl, W. (2009), 'Is the R&D behaviour of fast-growing SMEs different? Evidence from CIS III data for 16 countries,' *Small Business Economics*, **33**(1), 59-75.

Hölzl,W. (2010), 'The Economics of Entrepreneurship Policy: Introduction to the Special Issue,' *Journal of Industry, Competition and Trade*, **10**(3), 187-197.

Jaffe, A. (1986), 'Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value,' *American Economic Review*, **76**(5), 984-1001.

Jaffe, A. (1989), 'Real Effects of Academic Research,' *American Economic Review*, **79**(5), 957-70.

Katila, R. and Ahuja, G. (2002), 'Something old, something new: a Longitudinal Study of Search Behaviour and New Product Introduction,' *Academy of Management Journal*, **45**(6), 1183-1194.

Kauffman, S.A. (1993), *Origins of order: Self-Organization and selection in evolution*. Oxford University Press: Oxford.

Krafft, J. and Quatraro, F. (2011), 'The dynamics of technological knowledge: from linearity to recombination,' in Antonelli, C. (ed) *Handbook on the Economic Complexity of Technological Change*. Edward Elgar: Cheltenham.

Krafft, J., Quatraro, F. and Saviotti, P.P. (2009), 'Evolution of the knowledge base in knowledge intensive sectors,' LEI-BRICK Working Paper no 06/2009.

Krafft, J., Quatraro, F. and Saviotti, P.P. (2011), 'The knowledge base evolution in biotechnology: A social network analysis,' *Economics of Innovation and New Technology*, **20**, 445-477.

Lane, D.A., van Der Leeuw, S.E., Pumain, D., West, G. (eds.) (2009), *Complexity perspectives in innovation and social change*. Springer, Berlin.

Lee, K. (2010), 'A theory of firm growth: learning capability, knowledge threshold, and patterns of growth,' *Research Policy*, **39**, 278-289.

Lotti, F., Santarelli, E. and Vivarelli, M. (2003), 'Does Gibrats Law Hold Among Young, Small Firms?,' Journal *of Evolutionary Economics*, **13**, 213-35

Lotti, F., Santarelli, E. and Vivarelli, M. (2009), 'Defending Gibrat's Law as a Long-Run Regularity,' *Small Business Economics*, **32**, 31-44

Malerba, F. and Orsenigo, L. (1995), 'Schumpeterian Patterns of Innovation,' *Cambridge Journal of Economics*, **19**(1), 47-65.

Malerba, F. and Orsenigo, L. (1997), 'The Dynamics and Evolution of Industries,' *Industrial and Corporate Change*, **5**(1), 51-87.

Mansfield, E. (1980), 'Basic research and productivity increase in manufacturing,' *American Economic Review*, **70**, 863-73.

March, J. (1991), 'Exploration and exploitation in organizational learning,' *Organization Science*, **2**(1), 71-87.

Murmann, J.P. and Frenken, K. (2006), 'Towards a systematic framework for research on dominant designs, technological innovations, and industrial change,' *Research Policy*, **35**, 925-952.

Nelson, R.R. and Winter, S.W. (1982), *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Nesta, L. and Saviotti, P.P. (2005), 'Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the U.S. Pharmaceutical Industry,' *Journal of Industrial Economics*, **53**(1) 123-42.

Nesta, L. and Saviotti, P.P. (2006), 'Firm Knowledge and Market Value in Biotechnology,' *Industrial and Corporate Change*, **15**(4) 625-52.

Nesta, L. (2008), 'Knowledge and productivity in the world's largest manufacturing corporations,' *Journal of Economic Behaviour and Organization*, **67**, 886-902.

Nightingale, P. (1998), 'A cognitive model of innovation,' *Research Policy*, **27**, 689-709.

Nightingale, P. and Coad, A. (2014), 'Gazelles and MUPPETS: Ideological and Methodological Biases in Entrepreneurship Research,' *Industrial and Corporate Change*, this issue.

Nooteboom, B. (2000), *Learning and innovation in organizations and economies*, Oxford: Oxford University Press.

Ostergaard, C., Timmermans, B., and Kristinssson, K. (2011), 'Does a different view create something new? The effect of employee diversity on innovation,' *Research Policy*, **40**, 500-509.

Pakes, A., Schankerman, M. (1984), 'The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources,' in: Griliches, Z. (Ed.)., *R&D, Patents, and Productivity*. University of Chicago Press: Chicago.

Pakes, A. and Schankerman, M. (1977), 'A decomposition of the intraindustry and interindustry variance in research intensity in American manufacturing: Demand inducement, technological opportunity, and appropriability,' Harvard University. Manuscript.

Parker, S.C, Storey, D.J. and van Witteloostuijn, A. (2010), 'What happens to gazelles? The importance of dynamic management strategy,' *Small Business Economics*, **35**, 203-226.

Pavitt, K. (1985), 'Patent statistics as indicators of innovative activities: Possibilities and problems,' *Scientometrics*, **7**, 77-99.

Quatraro, F. (2010), 'Knowledge Coherence, Variety and Productivity Growth: Manufacturing Evidence from Italian Regions,' *Research Policy*, **39**, 1289-1302.

Saviotti, P.P. (1988), 'Information, variety and entropy in technoeconomic development,' *Research Policy*, **17**(2), 89-103.

Saviotti, P.P. (2004), 'Considerations about the production and utilization of knowledge,' *Journal of Institutional and Theoretical Economics*, **160**, 100-121.

Saviotti, P.P. (2007), 'On the dynamics of generation and utilisation of knowledge: The local character of knowledge,' *Structural Change and Economic Dynamics*, **18**, 387-408.

Scherer, F.M. (1982), 'Demand-Pull and Technological Invention: Schmookler Revisted,' *Journal of Industrial Economics*, **30**, 225-237.

Schmookler, J. (1954), 'The level of inventive activity,' *The Review of Economics and Statistics*, **36**, 183-190.

Schmookler, J. (1962), 'Economic Sources of Inventive Activity,' *The Journal of Economic History*, **22**, 1-20.

Schmookler, J. (1966), *Invention and Economic Growth*. Harvard University Press: Cambridge, MA.

Teece, D., Rumelt, R., Dosi, G. and Winter, S. (1994), 'Understanding Corporate Coherence: Theory and Evidence,' *Journal of Economic Behaviour and Organization*, **23**(1), 1-30.

Theil, H. (1967), *Economics and Information Theory*. Amsterdam: North Holland.

Thoma, G., Torrisi, S., Gambardella, A., Guellec, D., Hall, B.H. and Haroff, D. (2010), ' Harmonizing and combining large datasets – an application to firm-level patent and accounting data,' NBER Working Paper 15851.

Weitzmann, M.L. (1998), 'Recombinant growth,' *Quarterly Journal of Economics*, **113**, 331-360.

APPENDIX A – The properties of knowledge structure

Knowledge Variety

We measure variety in the firm's knowledge base using the information entropy index. Entropy measures the degree of disorder or randomness of the system, so that systems characterized by high entropy will also be characterized by high levels of uncertainty (Saviotti, 1988).

The index was introduced to economic analysis by Theil (1967). Its earlier applications aimed at measuring the degree of diversity of industrial activity (or of a sample of firms within an industry) against a uniform distribution of economic activities in all sectors, or among firms (Attaran, 1985; Frenken et al., 2007; Boschma and Iammarino, 2009).

Compared to common measures of variety and concentration, information entropy has some interesting properties (Frenken and Nuvolari, 2004). An important feature of the entropy measure, which we exploit in our analysis, is its multidimensional extension. Consider a pair of events (X_j, Y_m), and the probability of their co-occurrence p_{jm}. A two dimensional (total) entropy measure can be expressed as follows (firm and time subscripts are omitted for the sake of clarity):

$$H(X,Y) = \sum_{j=1}^{q} \sum_{m=1}^{w} p_{jm} \log_2 \left(\frac{1}{p_{jm}} \right) \tag{A1}$$

If p_{jm} is assumed to be the probability that two technological classes j and m co-occur within the same patent, then the measure of multidimensional entropy focuses on the variety of co-occurrences of technological classes within firms' patent portfolios.

Moreover, the total index can be decomposed in a 'within' and a 'between' part whenever the events to be investigated can be aggregated to form a smaller numbers of subsets. Within-entropy measures the average degree of disorder or variety within the subsets, between-entropy focuses on the subsets measuring the variety across them. It can be easily shown that the decomposition theorem also holds for the multidimensional case. Hence if one allows $j \in S_g$ and $m \in S_z$ (g = 1,…,G; z = 1,…, Z), we can rewrite *H(X,Y)* as follows:

$$H(X,Y) = H_Q + \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz} H_{gz} \tag{A2}$$

where the first term on the right-hand-side is the between-group entropy and the second term is the (weighted) within-group entropy. In particular:

$$H_Q = \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz} \log_2 \frac{1}{P_{gz}} \tag{A2a}$$

$$P_{gz} = \sum_{j \in S_g} \sum_{m \in S_Z} p_{jm} \tag{A2b}$$

$$H_{gz} = \sum_{j \in S_g} \sum_{m \in S_z} \frac{p_{ij}}{P_{gz}} \log_2 \left(\frac{1}{p_{jm} / P_{gz}} \right) \tag{A2c}$$

Following Frenken et al. (2007), we can refer to between-group and within-group entropy respectively as *unrelated technological variety* (*UTV*) and *related technological variety* (*RTV*), while total information entropy is referred to as *general technological variety (TV)*. The distinction between related and unrelated variety is based on the assumption that any pair of entities included in the former generally are more closely related or more similar to any pair of entities included in the latter. This assumption is reasonable given that a type of entity (patent, industrial sector, trade categories etc.) is organized according to a hierarchical classification. In this case each class at a given level of aggregation contains ‘smaller’ classes, which, in turn contain yet ‘smaller’ classes. Here, small refers to a low level of aggregation.

We can reasonably expect then that the average pair of entities at a given level of aggregation will be more similar than the average pair of entities at a higher level of aggregation. Thus, what we call related variety is measured at a lower level of aggregation (3 digit class within a 1 digit macro-class) than unrelated variety (across 1 digit macro-classes). This distinction is important because we can expect unrelated (or inter-group) variety to affect productivity growth negatively, while related (or intra-group) variety is expected to be positively related to productivity growth. Moreover, the evolution of total variety is heavily influenced by the relative dynamics of related and unrelated variety, such that if unrelated variety is dominant the effects of total variety on productivity growth can be expected to be negative, while the opposite holds if related technological variety dominates the total index (Krafft, Quatraro, Saviotti, 2011).

Knowledge Coherence

Third, we calculated the *coherence* (*R*) of firms' knowledge bases, defined as the average complementarity of any technology randomly chosen within the firm's portfolio with respect to any other technology (Nesta and Saviotti, 2005, 2006; Nesta, 2008).

To yield the knowledge coherence index, a number of steps is required. In what follows we describe how to derive the index at the firm level. First, we need to calculate the weighted average relatedness WAR_i of technology *i* with respect to all other technologies present in the sector. Such a measure builds on the measure of technological relatedness τ,. The calculation of such a measure builds on the relatedness matrix. The technological universe consists of *k* patent applications. Let P_{mk} = 1 if the patent *k* is assigned the technology m [*m* = 1, …, n], and 0 otherwise. The total number of patents assigned to technology *m* is $O_m = \sum_k P_{mk}$. Similarly, the total number of patents assigned to technology *j* is $O_j = \sum_k P_{jk}$. Since two technologies may occur within the same patent, $O_m \cap O_j \neq \varnothing$, and thus the observed the number of observed co-occurrences of technologies m and *j* is $J_{mj} = \sum_k P_{mk} P_{jk}$ .. Applying this relationship to all possible pairs yields a square matrix Ω (n × n) whose generic cell is the observed number of co-occurrences:

$$\Omega = \begin{bmatrix} J_{11} & & J_{m1} & & J_{n1} \\ \vdots & \ddots & & & \vdots \\ J_{1j} & & J_{mj} & & J_{nj} \\ \vdots & & & \ddots & \vdots \\ J_{1n} & \cdots & J_{mn} & \cdots & J_{nn} \end{bmatrix} \qquad \text{(A1)}$$

We assume that the number x_{mj} of patents assigned to both technologies *m* and *j* is a hypergeometric random variable of mean and variance:

$$\mu_{mj} = E(X_{mj} = x) = \frac{O_m O_j}{K} \qquad \text{(A2)}$$

$$\sigma_{mj}^2 = \mu_{ij} \left(\frac{K - O_m}{K} \right) \left(\frac{K - O_j}{K - 1} \right) \qquad \text{(A3)}$$

If the observed number of co-occurrences J_{mj} is larger than the expected number of random co-occurrences μ_{mj}, then the two technologies are closely related: the fact the two technologies occur together in the number of patents x_{ij} is not casual. The measure of relatedness hence is given by the difference between the observed number and the expected number of co-occurrences, weighted by their standard deviation:

$$\tau_{mj} = \frac{J_{mj} - \mu_{mj}}{\sigma_{mj}} \qquad \text{(A4)}$$

It is worth noting that our relatedness measure has no lower and upper bounds: $\tau_{mj} \in \left]-\infty; +\infty\right[$. Moreover, the index shows a distribution similar to a t-student, so that if $\tau_{mj} \in \left]-1.96; +1.96\right[$, one can safely accept the null hypothesis of non-relatedness of the two technologies *i* and *j*. The technological relatedness matrix Ω′ may hence be thought about as a weighting scheme to evaluate the technological portfolio of firms.

Following Teece et al. (1994), WAR_j is defined as the degree to which technology j is related to all other technologies $m \neq j$ within the firm i, weighted by patent count P_{mit}:

$$WAR_{jit} = \frac{\sum_{m \neq j} \tau_{jm} P_{mit}}{\sum_{m \neq i} P_{mit}} \qquad \text{(A3)}$$

Finally, knowledge base coherence within the firm is defined as the weighted average of the WAR_{jit} measure:

$$R_{it} = \sum_{j \neq m} WAR_{jit} \times \frac{P_{jit}}{\sum_j P_{jit}} \qquad \text{(A4)}$$

This measure captures the degree to which the technologies making up the firm's knowledge base are complementary. The relatedness measure τ_{jm} indicates that utilization of technology j implies utilization of technology m in order to perform specific functions that are not reducible to their independent use. This makes the coherence index appropriate for the purposes of this study.

Cognitive Distance

We implement a measure of knowledge similarity, proxied by cognitive distance (Nooteboom, 2000), which expresses the dissimilarities amongst different types of knowledge. A useful index of distance can be derived from the measure of *technological proximity*, originally proposed by Jaffe (1986, 1989), who investigated the proximity of firms' technological portfolios. Breschi et al. (2003) adapted the index in order to measure the proximity, or relatedness, between two technologies. The idea is that each firm is characterized by a vector V of the k technologies that occur in its patents. Knowledge similarity can first be calculated for a pair of technologies l and j as the angular separation or uncentred correlation of the vectors V_{lk} and V_{jk}. The similarities between technologies l and j can then be defined as follows:

$$S_{lj} = \frac{\sum_{k=1}^{n} V_{lk} V_{jk}}{\sqrt{\sum_{k=1}^{n} V_{lk}^2} \sqrt{\sum_{k=1}^{n} V_{jk}^2}} \tag{A5}$$

The idea behind the calculation of this index is that two technologies j and i are similar to the extent that they co-occur with a third technology k. The cognitive distance between j and i is the complement of their index of the similarity:

$$d_{lj} = 1 - S_{lj} \tag{A6}$$

Once an index is calculated for all possible pairs, it needs to be aggregated at the firm level to obtain a synthetic index of technological distance. This is done in two steps. First we compute the weighted average distance of technology *i*, i.e. the average distance of *i* from all other technologies.

$$WAD_{lt} = \frac{\sum_{j \neq l} d_{lj} P_{jit}}{\sum_{j \neq l} P_{jit}} \tag{A7}$$

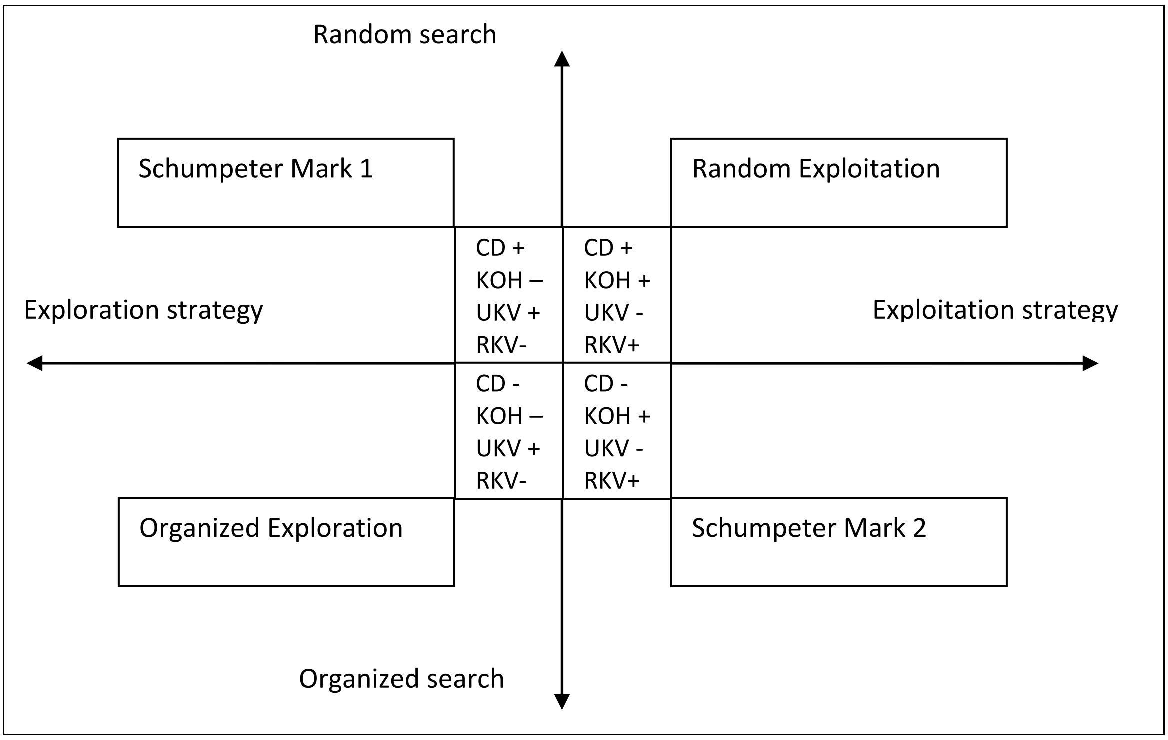
where P_j is the number of patents in which the technology *j* is observed. Then we can obtain the average cognitive distance at time *t* as follows:

$$CD_t = \sum_l WAD_{lit} \times \frac{P_{lit}}{\sum_l P_{lit}} \tag{A8}$$

Appendix B - Sectoral classification and concordance

Macro sectors	Sector	STAN (ISIC 3)	Datastream
High-technology manufactures HT	Pharmaceuticals	2423	4577
	Office, accounting and computing machinery	30	9572, 9574
	Radio, television and communication equipment	32	2737, 3743, 3745,3747,9576, 9578
	Medical, precision and optical instruments	33	4535, 4537, 4573
	Aircraft and spacecraft	353	2713, 2717
Medium-high technology manuf. MHT	Chemicals excluding pharmaceuticals	24ex2423	1353, 1357
	Machinery and equipment, n.e.c.	29	573, 583, 2757
	Electrical machinery and apparatus, nec	31	2733, 3722
	Motor vehicles, trailers and semi-trailers and other transport equipment, aircraft excluded	34, 351, 352-359	2753, 3353, 3355
Medium-low technology manuf. MLT	Coke, refined petroleum products and nuclear fuel	23	533, 537, 577, 587
	Rubber, plastics products and other non-metallic mineral products	25-26	2353, 2723, 3357
	Basic metals and fabricated metal products	27-28	1753, 1755, 1757
Low technology manufactures LT	Food products and beverages	15	3533, 3535, 3537, 3577
	Tobacco products	16	3785
	Textiles, textile products, leather and footwear	17-19	3763, 3765
	Pulp, paper and paper products	21	1737
	Printing and publishing	22	5557
	Manufacturing nec and recycling	36-37	2727, 3724, 3726, 3767
Knowledge intensive sectors KIS	Post and telecommunications	64	5553, 6535, 6575
	Financial intermediation (excl insurance, pension)	65	8355, 8773, 8779
	Insurance and pension funding	66	8532, 8534, 8536, 8538, 8575
	Activities related to financial intermediation	67	8775, 8777, 8985, 8995
	Real estate activities	70	8633, 8637, 8671, 8672, 8673, 8674, 8675, 8676, 8677, 8771
	Renting of m&eq and other business activities	71-74	2791, 2793, 2795, 2799, 5555, 9533, 9535, 9537
	Health and social work	85	4533
	Recreational cultural and sporting activities	92	5752, 5755
Less knowledge intensive sectors LKIS	Wholesale, trade (excl. Motor vehicles)	51	2797, 5379
	Retail trade; repair of household goods	52	5333, 5337, 5371, 5373, 5375
	Hotels and restaurants	55	5753, 5757
Other services OS	Transport and storage	60-63	2771, 2773, 2775, 2777, 2779, 5751, 5759
	Community social and personal services	75-99	5377
Energy producing activities EP	Mining, quarrying of energy producing materials	10-12	1771
	Mining, quarrying (excl energy)	13-14	1773, 1775, 1777, 1779
	Electricity, gas, and water supply	40-41	7535, 7537, 7573, 7575, 7577
Constr	Construction	45	2357, 3728

Figure 1



Note: The outer boxes refer to the possible innovation patterns described in Section 2. The inner boxes report the expected signs of the variables introduced in Section 3.2.

Figure 2 – Kernel density estimation of growth rates distribution of the main variables

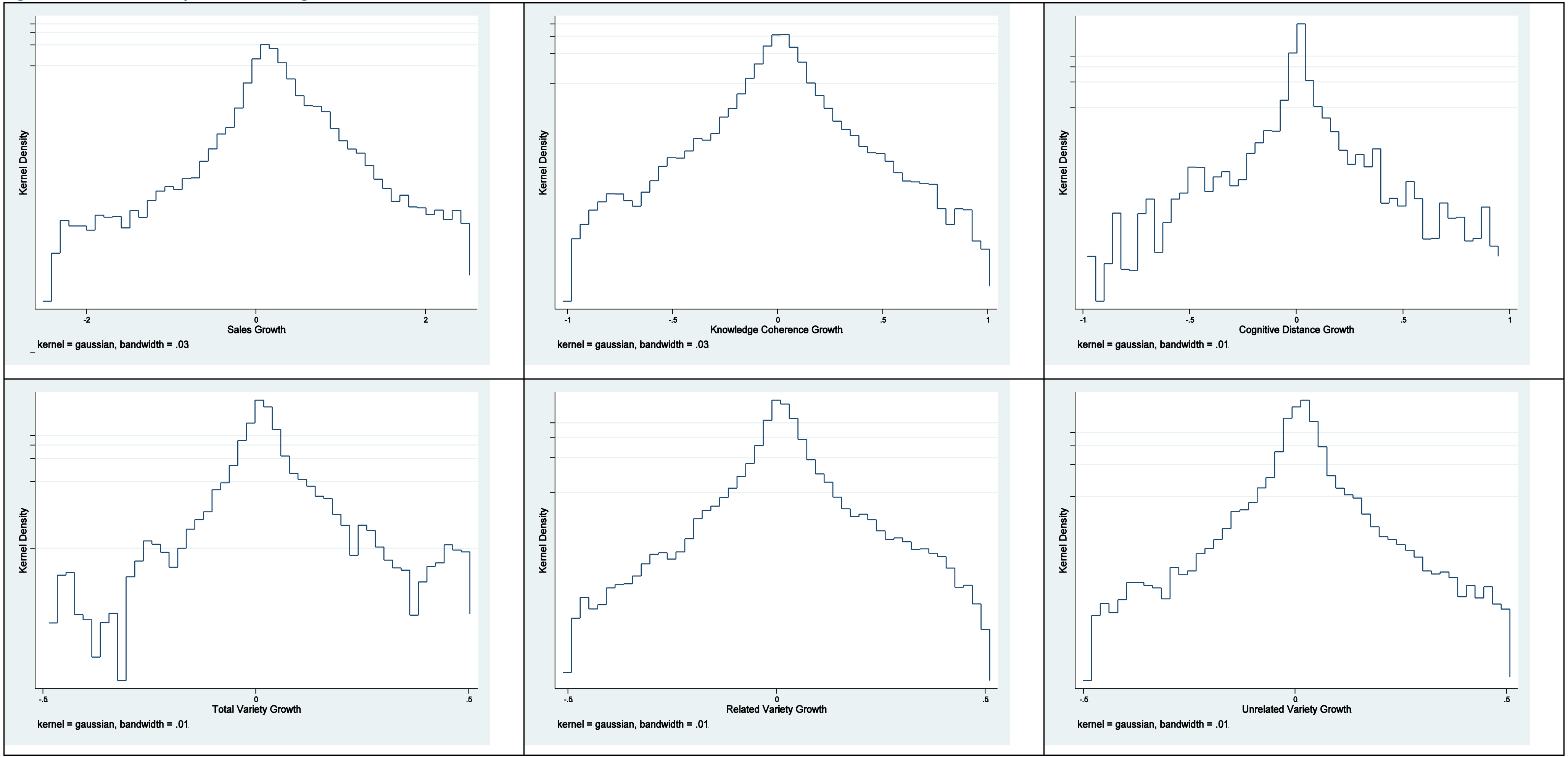
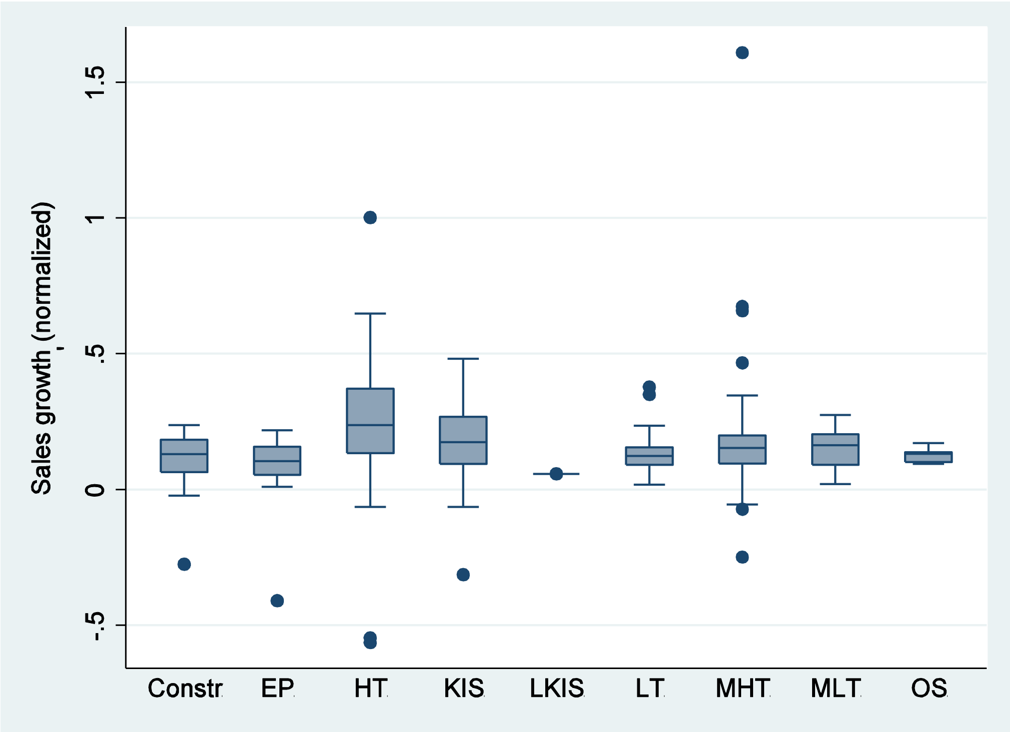


Figure 3 – Box plot of sales growth by macro-sector



Note: See Appendix B for the definition of macro-sectors.

Table 1 – Distribution of sampled firmsby macro-sector, size and country, 1988-2005

Macro Sector			Country			Size		
	Freq.	Percent		Freq.	Percent		Freq.	Percent
HT	102	30.45	France	83	24.78	Large	271	80.9
MHT	123	36.72	Germany	114	34.03	Medium	45	13.43
MLT	11	3.28	Italy	34	10.15	Micro	1	0.3
LT	34	10.15	Netherlands	13	3.88	Small	18	5.37
KIS	26	7.76	Sweden	43	12.84			
LKIS	1	0.30	UK	48	14.33			
OS	5	1.49						
Constr	23	6.87						
EP	10	2.99						
Total	335	100.00		335	100.00		335	100.00

Table 2 - Descriptive statistics (All variables are expressed in normalized growth rates according to Eq. 2).

	Std. Dev.	skewness	kurtosis	p10	p25	p50	p75	p90	Obs.
Sales Growth	0.395	1.716	33.500	-0.099	0.012	0.112	0.250	0.557	2819
Knowledge Coherence	0.353	-0.628	33.390	-0.288	-0.104	-0.007	0.089	0.285	2819
Knowledge Capital	0.178	2.351	13.146	-0.096	-0.032	0.041	0.138	0.272	2819
Cognitive Distance	0.242	0.278	11.531	-0.169	-0.032	-0.006	0.029	0.177	1448
Knowledge Variety	0.132	0.401	25.337	-0.058	-0.018	0.004	0.033	0.103	2554
Related Variety	0.231	0.553	10.983	-0.180	-0.049	0.001	0.067	0.235	2287
Unrelated Variety	0.167	0.088	10.986	-0.128	-0.031	0.006	0.043	0.151	2394

Table 3- Spearman's Rank Correlation Matrix

	Sales Growth	Knowledge Coherence	Knowledge Capital	Cognitive Distance	Related Variety	Unrelated Variety	Knowledge Variety
Sales Growth	1.0000						
Kn. Coherence	-0.0048	1.0000					
Knowledge Capital	0.0114	0.0862*	1.0000				
Cognitive Distance	-0.0212	0.0651*	0.0211	1.0000			
Related Variety	-0.0618*	-0.1138*	0.3226*	-0.0624*	1.0000		
Unrelated Variety	-0.0225	-0.1224*	0.1262*	-0.0428	0.3677*	1.0000	
Knowledge Variety	0.0124	0.0150	0.2184*	-0.0098	0.4753*	-0.3906*	1.0000

Note: * Significant at 5% level.

Table 4 – Results of VAR estimation, one-year lag. Baseline model (All variables are expressed in normalized growth rates according to Eq. 2).

	Sales Growth(t-1)	Knowledge Coherence (t-1)	Knowledge Capital (t-1)	Cognitive Distance (t-1)	Related Variety (t-1)	Unrelated Variety (t-1)	Knowledge Variety (t-1)	N. Obs.
Sales Growth	.101*** (.008)	.007 (.012)	-.103*** (.028)	.031* (.016)	-.026 (.039)	-.003 (.055)	.091 (.104)	1366
Knowledge Coherence	-.021*** (.007)	-.303*** (.009)	.035 (.022)	.016 (.013)	.072** (.031)	.113*** (.044)	-.282*** (.082)	1366
Knowledge Capital	.013*** (.003)	.006 (.005)	.699*** (.011)	.0001 (.006)	-.037** (.015)	-.044** (.022)	.119*** (.041)	1366
Cognitive Distance	-.008*** (.003)	.002 (.004)	.011 (.009)	-.013** (.005)	.004 (.014)	-.012 (.019)	.057 (.037)	1288
Related Variety	.0004 (.005)	.010 (.007)	.130*** (.017)	.020** (.010)	-.240*** (.024)	-.021 (.033)	.195*** (.063)	1366
Unrelated Variety	-.00006 (.004)	-.0001 (.005)	.004 (.013)	.003 (.008)	.042** (.019)	-.072*** (.027)	.015 (.051)	1366
Knowledge Variety	.005** (.002)	.001 (.003)	.081*** (.008)	-.010** (.004)	.026** (.011)	.036** (.016)	-.239*** (.030)	1366

Note: bootstrapped standard errors between parentheses. p<0.1; ** : p<0.05; *** : p<0.01.

Table 5 - Results of VAR estimation. One-year lag. Model including a dummy for HGFs (All variables are expressed in normalized growth rates according to Eq. 2).

	Sales Growth(t-1)	HGF (dummy)	Knowledge Coherence (t-1)	Knowledge Capital (t-1)	Cognitive Distance (t-1)	Related Variety (t-1)	Unrelated Variety (t-1)	Knowledge Variety (t-1)	N. Obs.
Sales Growth	.063*** (.009)	.218*** (.009)	.030** (.012)	-.097*** (.029)	.001 (.017)	.049 (.040)	.050 (.057)	-.066 (.107)	1366
Knowledge Coherence	-.020*** (.006)	-.008 (.006)	-.299*** (.008)	.031* (.019)	.018* (.011)	.062** (.026)	.094*** (.038)	-.262*** (.071)	1366
Knowledge Capital	.0137*** (.004)	.009** (.004)	.006 (.005)	.694*** (.012)	-.003 (.007)	-.025 (.018)	-.030 (.025)	.092** (.047)	1366
Cognitive Distance	-.009*** (.003)	-.005* (.003)	.002 (.004)	.011 (.009)	-.011** (.006)	-.006 (.014)	-.028 (.020)	.093** (.038)	1228
Related Variety	-.0002 (.005)	.001 (.006)	.010 (.007)	.129*** (.018)	.020* (.010)	-.236*** (.026)	-.018 (.036)	.187*** (.068)	1366
Unrelated Variety	-.0007 (.004)	.005 (.004)	.0004 (.006)	.010 (.014)	.0014 (.008)	.051*** (.020)	-.065** (.029)	-.011 (.054)	1366
Knowledge Variety	.005** (.002)	.002 (.003)	.001 (.003)	.081*** (.008)	-.009** (.004)	.025** (.011)	.035** (.016)	-.235*** (.031)	1366

Note: bootstrapped standard errors between parentheses. p<0.1; ** : p<0.05; *** : p<0.01.

Table 6 - Results of VAR estimation. One-year lag. Model including both the HGFs dummy and the interaction term (All variables are expressed in normalized growth rates according to Eq. 2).

	Sales Growth(t-1)	HGF (dummy)	HGF*Growth	Knowledge Coherence (t-1)	Knowledge Capital (t-1)	Cognitive Distance (t-1)	Related Variety (t-1)	Unrelated Variety (t-1)	Knowledge Variety (t-1)	N. Obs.
Sales Growth	.075*** (.011)	.232*** (.010)	-.043** (.021)	.034*** (.013)	-.097*** (.030)	.001 (.017)	.056 (.042)	.058 (.060)	-.080 (.112)	1366
Knowledge Coherence	-.035*** (.007)	-.013* (.008)	.031** (.015)	-.307*** (.010)	.031 (.022)	.018 (.013)	.059* (.031)	.097** (.045)	-.250*** (.085)	1366
Knowledge Capital	.017*** (.004)	.009** (.004*	-.005 (.009)	.007 (.005)	.698*** (.012)	-.003 (.007)	-.028* (.017)	-.031 (.025)	.094** (.046)	1366
Cognitive Distance	-.007** (.003)	-.004 (.003)	-.004 (.007)	.003 (.004)	.010 (.010)	-.012** (.006)	-.004 (.015)	-.027 (.021)	.089** (.040)	1228
Related Variety	.013** (.006)	.005 (.006)	-.027** (.013)	.011 (.007)	.135*** (.018)	.023** (.010)	-.231*** (.025)	-.018 (.036)	.162** (.068)	1366
Unrelated Variety	-.0009 (.005)	.004 (.005)	.004 (.010)	.0003 (.006)	.008 (.015)	.002 (.009)	.044** (.021)	-.063** (.030)	-.002 (.056)	1366
Knowledge Variety	.009*** (.003)	.002 (.003)	-.009* (.006)	.001 (.003)	.078*** (.008)	-.010** (.005)	.031*** (.012)	.043*** (.017)	-.244*** (.032)	1366

Note: bootstrapped standard errors between parentheses. p<0.1; ** : p<0.05; *** : p<0.01.